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S.I.: DESIGN AND MANAGEMENT OF HUMANITARIAN SUPPLY CHAINS

Management of humanitarian relief operations using satellite big data analytics: the case of Kerala floods

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Abstract

Disasters lead to breakdown of established Information and Communication Technology (ICT) infrastructure. ICT breakdown obstructs the channel to gather real-time last mile information directly from the disaster-stricken communities and thereby hampers the agility of humanitarian supply chains. This creates a complex, chaotic, uncertain, and restrictive environment for humanitarian relief operations, which struggles for credible information to prioritize and deliver effective relief services. In this paper, we discuss how satellite big data analytics built over real-time weather information, geospatial data and deployed over a cloud-computing platform aided in achieving improved coordination and collaboration between rescue teams for humanitarian relief efforts in the case of 2018 Kerala floods. The analytics platform made available to the stakeholders involved in the rescue operations led to timely logistical planning and execution of rescue missions. The developed platform improved the accuracy of information between the distressed community and the stakeholders involved and thereby increased the agility of humanitarian logistics and relief supply chains. This research proves the utility of fusing data sources that are normally sitting as islands of information using big data analytics to prioritize humanitarian relief operations.

Keywords Humanitarian relief operations · Information and communications technologies · Agility · Satellite big data analytics · Disaster management

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1 Introduction

The very nature of sudden disasters is their unannounced onset at an unpredictable time and location, and is characterised by insufficient knowledge on its intensity (Day et al. 2012). The cycle of humanitarian operations involved in disaster management mostly fall into the categories of preparedness, emergency relief, rehabilitation and development (Kovács and Spens 2013). Humanitarian and emergency logistics suffer from the lack of real-time information or communication with the disaster victims which leads to poor predictability of demand, improper coordination of supply, and inability to achieve last mile operations (Kovács and Spens 2007).

Uncertainties that challenge the stakeholders involved in disaster response is built on the lack of readily available credible information in disaster-prone areas on the population characteristics, the extent of damage, and the post-disaster infrastructure status (Balcik et al. 2010). Uncertainties as a part of rescue operations during the floods can be very diverse such as lack of information on the affected population in the high-risk zones (de Assis Dias et al. 2018) and challenges in routing that is inclusive of evacuee demographics (Esposito Amideo et al. 2019). Use of credible information can help reduce vulnerability of individuals in disasters (Zhu et al. 2011). Complexities increase due to absence of coordination between actors (Kabra et al. 2015) and with challenges of dealing with social media reported misinformation (Paul and Sosale 2019). The ability to deploy resources available in hand during the relief operations is heavily dependent on the accuracy of the available information on the disaster-stricken areas (van der Laan et al. 2009). These challenges point to the critical importance of information flow during relief operations.

Enhancing the overall accuracy and the availability of the information is the necessary foundation to increase the agility in humanitarian relief operations. Decision-making in humanitarian logistics and supply chains can benefit from utilisation of Information and Communication Technologies (ICTs) as they provide the ability to react more effectively and efficiently (Dorasamy et al. 2013; Kabra and Ramesh 2015). There is immense value in building better information generating and processing capabilities as it is expected to improve the effectiveness of coordination, cooperation and collaboration during humanitarian relief operations (Dubey et al. 2019). ICTs are attempting to provide dynamic sensing, dynamic speed and dynamic flexibility, which are essential to improving the agility in humanitarian relief operations (Dubey and Gunasekaran 2016). Limited use of ICT by the disaster responders decreases the agility of the humanitarian relief operations (Sharkey Scott et al. 2010). More recently, researchers have presented the value of diffusion of new technologies such as social media (Fosso Wamba et al. 2019; Liu et al. 2016; Lee and Tapia 2015; Kongthon et al. 2014), internet-based tools (Han et al. 2019; Sinha et al. 2019; Shibuya 2017), and drones (Kim et al. 2019) to improve the information availability and overall effectiveness of response and recovery efforts.

Information as a apart of such intelligent process-aware ICTs[1] are said to support agility in disaster relief operations (Rasouli 2018). However, disasters such as floods can knock out the basic ICT infrastructure and provide no connectivity to the affected population to report their status. By studying the floods in Jammu and Kashmir in India, Dey (2017) discussed how the administration of the state got dysfunctional due to the inability to gather ground truth directly from the affected, primarily attributed to the absence of connectivity. It also

[1] Intelligent process-aware ICTs in the context of humanitarian relief operations refers to the development of tailor-made technology solutions that cater specifically to the needs of disaster management.

caused severe spill over problems in coordination, cooperation, and collaboration within the different services of the administration (e.g. control room, hospitals, police, etc.).

According to Indian disaster relief operations experience, novel information technology enabled models can be integrated using ICTs for better coordination (Gupta et al. 2016). There are new efforts that use technologies such as social media (Middleton et al. 2014) and digital/internet-driven networks (Yoo et al. 2016; Tim et al. 2017) that are contributing to reducing the response time in disaster rescue and relief operations. However, in their recent review of use of such technologies in disaster rescue and relief operations in India, Giri and Vats (2019) point to challenges in using such platforms including the lack of penetration of internet in rural areas, network connectivity problems in several geographies, large segments of strata in the society unaware of use of social media and absence of training to professionals involved in disaster relief operations on leveraging tools such as social media.

Satellite data has the potential to overcome these limitations. Specifically, satellite data when combined with other allied data sources such as census data can act as a potential source to bridge the gaps in information flows during rescue operations. To understand the fit between satellites and big data analytics, it might be useful to compare it with the fundamentals of what is characterized as big data. Volume, variety, and velocity are presented as the three dimensions of big data (Lee 2017). Satellite data has all these three dimensions. For instance, the Copernicus program of the European Commission with its Sentinel satellites produces approximately 10 TB of Earth Observation data per day which is available publicly for free (Kempeneers and Soille 2017). Chi et al. (2016) explain how multiple sources of information (different types of sensors satellites are carting such as lasers, radars, cameras, etc.) collected over multiple time periods at multiple scales (e.g. size of car to an entire block seen from space) adds variety in satellite big data. The velocity is arising from the fact that hundreds of satellites are now being deployed in space to beam data to the ground on an hourly basis. For example, a single company called Planet has deployed over 350 satellites since 2013 collecting over 250 million square kilometer of data everyday.[2] Therefore, satellites can be classified as a source of big data which can be used to improve the accuracy, completeness and consistency of information to facilitate better decision making. This enables ICT solutions to be built on top of this information which can ultimately help in humanitarian relief operations. Our paper documents how satellite big data can be deployed for immediate rescue operations using a real-life disaster incident in India. The overarching research question (RQ) that this study attempts to answer is stated below:

> **RQ** How 'passive' ICTs using satellite big data analytics can be leveraged to increase agility in humanitarian relief operations by overcoming the information obstruction created due to the breakdown of regular ICT during the disaster?

By employing a single case study methodology, we study the 2018 Kerala floods and document the real-life experience of deploying satellite imagery based big data analytics by collaborating with an Indian firm named 'SatSure'. By not getting into the technical details of the deployment (beyond the scope of this study), we demonstrate how the application of the satellite big data analytics acted as an alternative ICT to support the rescue efforts within the context of humanitarian relief operations. By 'passive' ICTs, we explicitly are looking at a case where there is no participation by the affected people because of their inability to access ICTs and none of the prepositioned ICTs in the affected geography are providing information on the status of the affected region.

[2] Information on Planet's satellite fleet is available on https://www.planet.com/faqs/ (last accessed on 08 March 2020).

To our knowledge, this is perhaps the first attempt in India that such a data fusion approach has been used for leveraging ICTs in humanitarian relief operations. The final solution is built using satellites as a primary data source and cell phone records, census and digital elevation models as secondary data sources. The final solution comprises of a common platform through which humanitarian relief operations team can plan and coordinate rescue efforts. The architecture of the solution is such that the results of satellite big data analytics provides rescue workers a passive ICT infrastructure that speaks to them on the intensity of the disaster, spread of the displaced persons and enables the planning of logistics for reaching the displaced. Our study provides a real-life context to the theoretical analysis of agility in humanitarian supply chains (Singh et al. 2018; Dubey et al. 2014). It also extends the feasibility for better information diffusion among agents involved in humanitarian operations (Altay and Pal 2014).

This paper is organised as follows. We introduce the role of ICTs in humanitarian relief operations and explain its importance in agility of humanitarian supply chains. We then highlight the application of big data in the context of humanitarian relief operations thus far and provide an insight into how satellites have been contributing to disaster management. Following it, we present the research gaps and discuss briefly how our case study research at the interface of satellite big data analytics and humanitarian relief operations (especially in the rescue planning and coordination) addresses the gaps identified. The results and the research findings are discussed in the light of the underlying technology allowing to overcome the information obstruction created by breakdown of regular ICT for the stakeholders involved. The paper concludes providing an overview of what the future holds in for a global adoption of satellite big data analytics as an integral part of ICTs to support humanitarian relief operations.

2 Literature review

Effective handling of disaster management operations require collaborative and strategic planning (Garnevska et al. 2012). In humanitarian relief operations, it is more important to catalyse exchanges and reciprocation between actors involved (Oloruntoba et al. 2016). ICTs support these transactions by providing a paradigm shift via a technology-driven approach which allows stakeholders in relief operations to be proactive (Kaur and Sood 2019). ICTs for disaster management is often viewed as technologies deployed to prepare and be as part of relief operations. ICTs in relief operations help in establishing contact with disaster affected populous. It can also be a tool that can be used post-disaster to assist in coordination and processing efforts of the rescue and rebuild teams. However, there is limited use of ICTs in disaster management operations due to the lack of real-time data and absence of systems satisfying interoperability standards within humanitarian organisations (Özdamar and Ertem 2015). Effective integration of ICTs in disaster management can remove such fragmentation of efforts in relief operations.

Within the Indian context, a study on the relief operations to heavy floods caused by cloud burst in Uttarakhand (Northern state in India) in June 2013 indicates that the lack of investment in disaster relief ICT created hindrance in the operations (Kabra et al. 2015). Moreover, lack of such investment in disaster preparedness by policymakers in India is shifting the onus to citizens themselves. For example, Choudhary and Vyas (2020) discuss employing mitigation techniques at the citizen level by building barriers such as sandbagging their homes, sealing walls with waterproofing compounds, raising the height of electric panels, etc. Essentially, any measures including leveraging ICTs in relief operations are to increase efficiency in rescue efforts to effectively reduce the causalities in a disaster (Zhang et al. 2018).

Disasters often lead to breakdown of the most basic elements of the technical infrastructure such as power lines that help channel the information (Sabbaghtorkan et al. 2019). For example, hurricane Katrina took out the entire communications infrastructure of the City of New Orleans leading to loss of coordination among the communities. It also led to a collapse of interorganizational response leaving them with no clarity on planning and executing relief operations (Comfort and Haase 2006). Therefore, disasters such as floods can wipe out the very backbone of every day ICT infrastructure. Planned benefits of pre-positioned technologies for ICT that depend on such basic technical infrastructure may deem completely dysfunctional during relief operations (Carroll and Neu 2009). Therefore, the type of ICTs that are planned to be used during disaster relief operations need to take the effect of disasters on the infrastructure hosting them.

The concept of agility in humanitarian relief operations is often discussed with a motivation to bring about increased efficiency in rescue efforts. The benefits of using ICTs for embracing agile principles in humanitarian relief operations have been acknowledged (Conforti et al. 2012). Effectively transferring established practices from commercial supply chains to humanitarian activities by integrating ICTs can help in embracing adaptability, flexibility, efficiency and efficacy (Abidi et al. 2014; Pettit and Beresford 2009; Balcik and Beamon 2008). From a supply chain perspective, one of the fundamental differences between commercial and humanitarian supply chains is the stable communications in the latter (Olaogbebikan and Oloruntoba 2019). Based on the arguments already stated, it is evident that agility in disaster relief operations is negatively impacted by loss of communication between the affected and the relief organizations.

This phenomenon is also reported in real-world incidents. For example, a complete communication collapse due to floods was witnessed during the catastrophic Jhelum floods in September 2014 in the state of Jammu & Kashmir in India (Bhatt et al. 2017). In such a state, the communities in majorly affected regions become largely 'voiceless' and passive in communication with humanitarian relief organizations. Big data is one such technology that is increasingly featured as a necessary pillar of agile supply chain management and can be explored as a part of humanitarian relief operations (Iqbal et al. 2018; Wang et al. 2016). Big data has been identified as a humanitarian technology which can be a part of crisis solutions and contribute to improving the quality of the entire cycle of activities in disaster management (Sandvik et al. 2014). Inherent characteristics of big data such as volume, velocity, veracity and the value are touted to give voice to the voiceless in the context of humanitarian supply networks (Monaghan and Lycett 2013). We would highlight that new technologies such as big data analytics are emerging as a part of decision support system in planning, coordination and management of humanitarian relief operations (Gupta et al. 2017).

Satellite imagery is one such big data when combined with other allied data sources such as census data can act as a potential source to bridge the gaps in information flows as part of the efforts in buttressing the humanitarian supply chain in disaster relief operations (Sodhi and Tang 2014). The Copernicus program of the European Commission with its Sentinel satellites produces approximately 10 TB of Earth Observation data per day (Kempeneers and Soille 2017). There is tremendous potential for such novel ICTs to be deployed for immediate rescue operations that does not rely on active information supply by the disaster affected populous but use technology to create a 'passive' voice for the affected.

In a recent study that captures lessons from disaster in Ghana, Owusu-Kwateng et al. (2017) specifically make a case for the criticality of response time in relief operations. Connecting big data analytics to humanitarian supply chain, Prasad et al. (2018) call for studies which can examine realistic scenarios to study the application of big data analytics and its outcomes. There is also substantial interest in understanding how big data is used in the context of immediate response phase (Chiappetta Jabbour et al. 2017). Large amounts of evidence and arguments placed so far has been conceptual or anecdotal (Kovács and Oloruntoba 2015; Abidi et al. 2014; Swaminathan 2017). We have recently started to witness the emergence of some empirical tests of the contribution of big data to existing humanitarian supply chains (Dubey et al. 2018; Papadopoulos et al. 2017).

Our objective is to study the application of big data analytics, which uses satellite imagery as a foundation, into the realm of agility in humanitarian relief operations. We also reflect on the quality of the information provided by satellite big data analytics and its effect on the relief operations (Najjar et al. 2019). In summary, there are challenges such as complete collapse of communication infrastructure that have affected disaster relief operations during floods in India. This in rendering the communities in majorly affected regions become largely 'voiceless' and passive in communication with humanitarian relief organizations. The concept of agility in humanitarian relief operations is often discussed in theoretical frameworks and is missing out on insights from real-life incidents. Big data has been identified as a humanitarian technology, but satellite data has not found its way into supporting immediate rescue operations to reduce response time and improve agility. Inspired by lessons from rescue operations for recent floods in India, we study the deployment of satellite big data analytics that does not rely on active information supply by the disaster affected populous but use technology to create a 'passive' voice for the affected.

3 Methodology

To answer the research question, we adopt case study methodology as discussed by Eisenhardt (1989) and Yin (1994) and utilise the experiences during the humanitarian relief operations for the 2018 Kerala floods. The case study is not randomly sampled, but rather chosen based on how they contribute to the research question itself (Siggelkow 2007). In studying the effect of information systems on users, organisations or the society, Kaplan and Duchon (1988) do not rule out case studies despite various normative nature of methodological points. Specifically, in the ICT innovation context, the choice of case studies is not new (Malhotra et al. 2001; von Krogh et al. 2003). Case study is an appropriate methodology to answer "how", "what" and "why" form of research questions (Yin 1994). The single-case study chosen in this study allows us to focus on conducting an analysis of the changes in the agility of humanitarian relief operations on utilising satellite big data analytics as a novel ICT. Ketokivi and Choi (2014) strengthen our choice of case study methodology and selection of case. Our research elaborates existing frameworks as it focuses on contextualised logic (i.e. humanitarian relief operations) of a general theory (i.e. agility and analytics). We investigate the general theory of agility and analytics and the context of humanitarian relief operations simultaneously, in a balanced manner. The selection of the case study approach allows us to set the research boundary to humanitarian relief operations and the case boundary specifically to the Kerala floods of 2018. This allows us to review the research gaps around agility in humanitarian relief operations by overcoming the information obstruction created due to the breakdown of regular ICT.

Our choice of a case study also finds support in recent literature of both humanitarian supply chain management and big data analytics. Behl and Dutta (2018) conducted a thematic literature review on a sample of 362 papers published between 2011 and 2017 in humanitarian operations and supply chain management. Their work provides evidence that case studies are highly sought after by academic researchers especially in the field of humanitarian operations. They report that case studies enabled researchers to study the success or failure of relief operations. Researchers get an opportunity to provide stakeholders solutions based on studying each one of them. Further, it contributes to theory building and empirical validation of such theories. Similarly, in a systematic literature review that touches upon the use of big data in disaster management, Akter and Wamba (2017) mention the lack of case studies in the realm of usage of big data in real life incidents.

We adopted convenience sampling while selecting Kerala floods as the case study. Convenience sampling technique is well adopted in general operations management literature (e.g. Barratt et al. 2011) and within humanitarian operations literature (e.g. Rajakaruna et al. 2017). Floods are one of the most prominent disasters in India (Mishra and Shah 2018). The convenience sampling of 2018 Kerala floods was based on several local factors that bridge the research team and the teams involved in the relief operations. This include proximity of the research team to Kerala and the ability to work closely with the local disaster management and humanitarian organisations involved in the relief operations. It is important to note that the key metric for success in the development of any such novel solutions for humanitarian relief operations largely depends on their adoption (Adner 2013). One of the biggest factors contributing to the choice of Kerala is that the authors and the research team could leverage their social capital for the trials and adoption of the solution. Principally, the solution approach discussed in this research can be replicated across different flood scenarios in India, but the contingency will pitch in the approval process for adoption of the technology.

3.1 Case study: 2018 Kerala flood

The measurements made by India Meteorological Department (IMD) reported a 42% above the normal rainfall activity in Kerala from 1 June 2018 to 19 August 2018 (Anandalekshmi et al. 2019). Studying the precipitation over Kerala during this period using weather data, Viswanadhapalli et al. (2019) report first and the second spell of rainfall was as high as 450 mm and 950 mm in some regions. The amount of rainfall equates to receiving 30% of annual rainfall within a matter of days (Surendran et al. 2019). Kerala had a State Disaster Management Plan that takes into account the incidence of floods. Floods in Kerala had become more frequent and severe that even made the Department of Revenue to assign a nodal body for flood hazard management (Kerala State Disaster Management Authority, 2011). A United Nations and European Commission collaborative study identified one of the bottlenecks in the relief operations was due to the disruption of power supply and snapping of communication links in several areas (UNDP 2018).

Figure 1 represents the official data from the Indian Metrological Department which measured a 164% increase in total amount of rainfall above the normal between 1 and 19 August 2018 in Kerala (India Meteorological Department 2018). The unusual rainfall pattern in Kerala began in the evening of 8 August 2018 and quickly escalated to overflow of dams in across the State of Kerala. The first movement of people into relief camps occurred on 9 August 2018. There was some respite on 12 August 2018 when the rainfall died. However, the intense and wide-spread showers resumed on 15 August 2018 across the State of Kerala. This led to the revamping of humanitarian relief operations for supporting the rapidly increasing amount of people affected by the floods.

Satellite big data analytics was suggested as a possible ICT tool to the administration of the Government of Kerala to aid in the humanitarian relief operations. The officials of the State

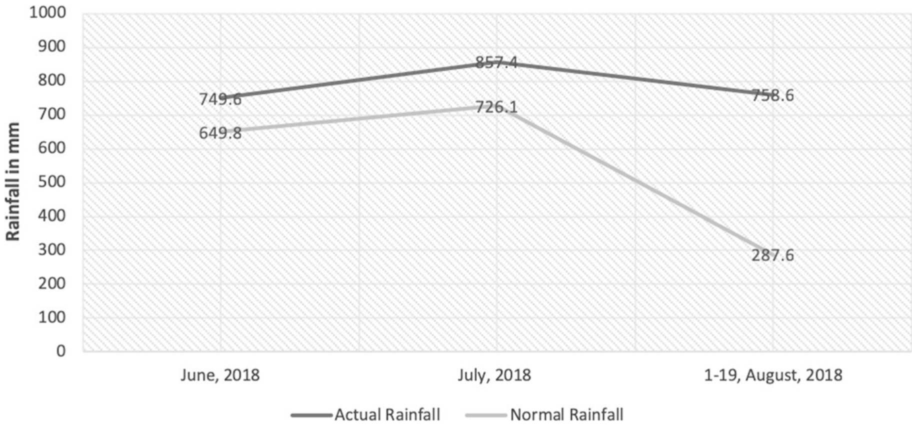


Fig. 1 Rainfall deviation over Kerala

of Kerala were keen on adopting the technology as a tool for supporting the humanitarian relief operations. The big data analytics platform was immediately deployed on 15 August 2018 and was made available to the humanitarian relief operations team. The rains receded on the 19 August 2018 in most parts of Kerala and the big data analytics platform recorded the data through 8 August 2018 to 21 August 2018. The satellite big data analytics solution for the rescue operations was used between 15 August 2018 to 22 August 2018.

4 Data

Table 1 provides an overview of the data sources used as input to conduct the satellite big data analytics. The data sources were deployed over a cloud-computing platform with an intent to achieve improved coordination and collaboration between rescue teams for humanitarian relief efforts in the case of Kerala floods in 2018. The data was collected in retrospect of setting the research boundary to humanitarian relief operations and the case boundary specifically to the Kerala floods of 2018. *SatSure* was the collaboration partner responsible for the technical implementation of fusing all the data sources. We collected data from the reports of Satsure and combined it with the perspectives of their employees and policymakers of the Government to Kerala. This allowed us to be in involved in studying the architecture, adoption, implementation and performance to gather information for answering the research question raised. The major sources of data and the analysis used in this paper are based on independent sources which allow the implementation of the solution in any other flood incident and geography. The methodology used in the analysis and the findings are not restrictive to the incident of Kerala floods in 2018 alone. In fact, the incident only provides a vantage point from where we discuss the findings and implications for agility in humanitarian relief operations. The choice of the factors, operationalisation of the data, and detailed description of the analysis ensures repeatability of the research conducted for any other flood incidents. These account for credibility of data sources as well as transferability, dependability and confirmability for any future studies adopting the same process. Therefore, our research satisfies the validly constructs laid down by Runeson and Höst (2008) as an extension to the use of case studies by Yin (1994).

Table 1 Data sources

Sources of data	Primary value of the data	Data provider	Analytics platform integration
Satellite data	Synthetic Aperture Radar (SAR) satellites can look through the clouds and still image the ground truth of the disaster affected areas	Open source data from Europe's Copernicus Sentinel SAR satellites and commercial high-resolution data	The satellite data is hosted on a cloud-server where the big data analytics algorithms run on them and the end analysis is provided over a web browser
Weather data	Data from automatic weather stations are able to provide rainfall recorded at the installed locations accurately and at frequent intervals	Geocode (latitude and longitude) based weather observations and forecasts sourced from a commercial weather services provider	The Application Programming Interface (API) is consumed within the big data analytics platform and includes data to keep track of intensity of rainfall over time
Geographic Information System (GIS)	Allows layering of spatially distributed information on maps. Digital Elevation Models provide critical three-dimensional representation of the terrain by adding the critical height information to the surface	GIS data was sourced and the mapping platform was provided by a commercial GIS services provider	The geo-analytics data used in the platform includes basemaps of the flood affected region, demographic data and industry specific layers
Census records	Localisation of the worst hit areas can be identified by collating the census data with the data on the intensity based on geographic location	The population estimates were provided by the Government of Kerala	The concentration of the population based on geolocation was integrated into the basemaps of the geographic area
Mobile phone call reports	Based on the availability of the connectivity, mobile phone call reports are fed to record status immediate surroundings by those reporting	The caller reports were collected and logged by the rescue teams setup by the Government of Kerala	Tagging of the reports based on estimated geolocation was integrated into the big data analytics platform

Synthetic Aperture Radar (SAR) satellites operate using microwaves, which brings them an ability to image day and night. They also have a special ability to see through clouds and heavy rainfall which makes them an important part of information gathering in disaster management (Schlaffer et al. 2015). These satellites provide the ability to seek the ground truth of the affected areas and can help estimate the intensity and the extent of damage caused by floods (Matgen et al. 2011). Sourcing of the SAR satellite data can be done through commercial procurement of imagery, using open/free-of-charge platforms such as the European Copernicus Sentinel constellation (Clark 2017), or can be requested through international initiative such as the United Nations Platform for Space-based information for Disaster Management and Emergency Response (UN-SPIDER), and Sentinel Asia led by the Asia–Pacific Regional Space Agency Forum (APRSAF) (Boccardo and Giulio Tonolo 2015).

Automatic Weather Stations (AWS) have become a critical component of disaster management as a localised rainfall measurement sensor. AWS helps in keeping a tab on the intensity of rainfall, which can then be used to issue alerts to rescue teams (Ahammed et al. 2014). In India's own experience of the 2005 Mumbai floods, the committee reviewing the disaster preparedness laid down recommendations for implementation of AWS. The installed AWS is capable of giving rainfall data every minute including the features such as audible alarm system at a preset rainfall intensity values. Such AWS have been installed across India to be able to capture rainfall data over most of the catchments (Gupta 2007). There has been a drive to provide the weather information over software APIs so that it can be consumed in big data analytics platforms. One such commercial API stream that provides temperature, precipitation, wind direction, wind speed, humidity, barometric pressure, dew point, and visibility was consumed on the big data analytics platform developed.

Geographic Information System (GIS) platforms allow layering of spatially distributed information on maps, which adds to the richness of the big data analytics. For example, hospitals across the State of Kerala were geolocated and tagged in the GIS. This helped humanitarian relief operation teams to transport any disaster victims needing medical attention to the nearest functioning hospitals. One of the critical sources of information needed to estimate the possible water logging is the three-dimensional terrain profile of the affected areas. This information is solicited using Digital Elevation Models (DEM), which are used to describe the terrain elevation data in a digital form and is used commonly as a part of the GIS in emergency management (Ertug and Kovel 2000). The application of DEMs in flood-related disaster management is in using a three-dimensional representation of the Earth's surface to determine the probable flood-affected areas through a time-series analysis of the rainfall inundation information from the onset to the passing of the flooding (Zerger and Wealands 2004). Both these datasets were hosted on the developed big data analytics platform to provide useful assessment of the water inundation and location of critical establishments such as hospitals.

Census data provides an estimation of the distribution of the inhabitants over a region and traditionally have been used in information flows for humanitarian supply chains in relief and recovery efforts (Sodhi and Tang 2014). Although census information may not be useful since the onset of a hazard may have alarmed local communities who may have then sought refuge by displacing themselves to safer zones. However, census data has been proven to be relevant in modelling for evacuation flow plans in events of short-term preparedness (Mejia-Argueta et al. 2018). Census data was integrated into the big data analytics platform to understand the distribution and the dispersal of the inhabitants in the worst affected areas.

Rescue phone lines were setup by the Government of Kerala so that those affected and still had mobile phone connectivity can reach out for help. The operators receiving the phone calls tried to effectively estimate and record the geolocation based on the description provided by the callers. The estimated geolocation could then be tagged in the big data analytics platform to highlight the information to the humanitarian relief operations teams.

5 Analysis

The data analysis began from collecting pre-disaster legacy data of the entire State of Kerala to build the baseline to begin the big data analytics process. This involved collecting the established data sources such as the basemaps of the entire State of Kerala that includes road connectivity information, village and district boundaries. This acts as the bottom layer of information on which new layers of data are transposed to create information of relevance for humanitarian relief operations. The basemaps are essentially two-dimensional data, which provides information on the length and breadth of the spread of geography. They do not provide any information on the change in elevation in the geography. The elevation of the geography is important to assess the possible flow of water and in identifying the plausible pockets of inundation of rain water. The elevation information is sourced from the DEM.

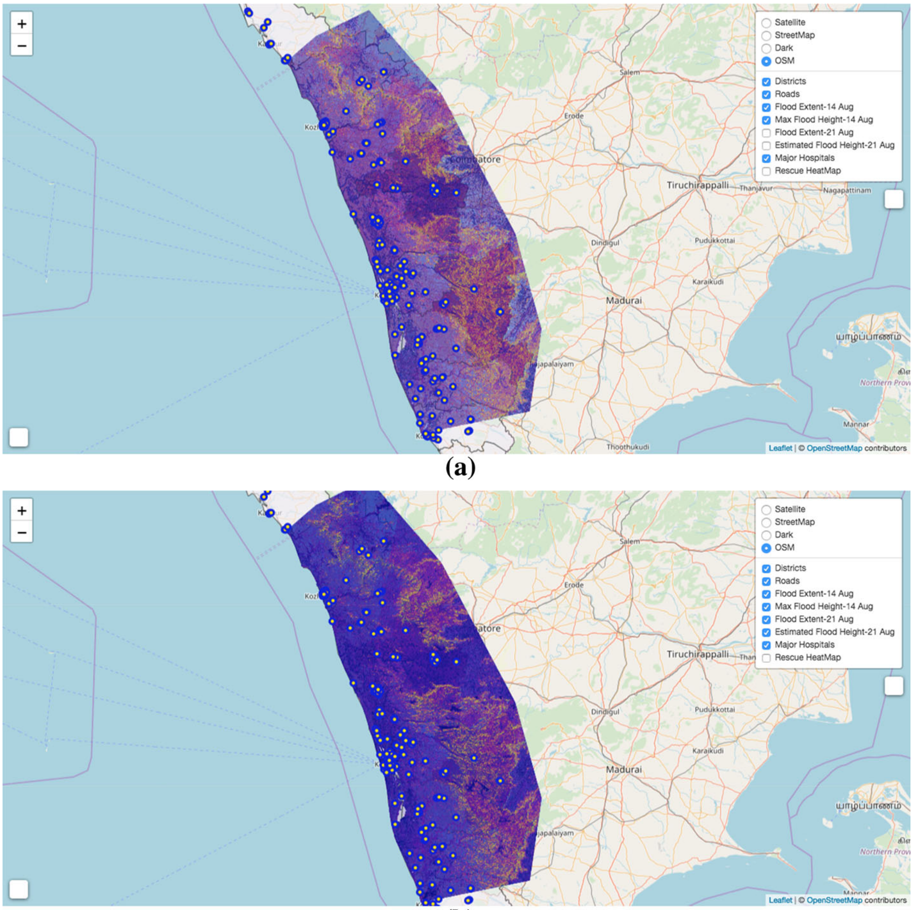
Once this process of preparation of the geo-surface information was completed, the exercise of geolocating critical establishments such as hospitals using the latitude and longitude information was prioritised. This is a process of building up geographic intelligence with data sources relevant to humanitarian relief operations. The information of hospitals was solicited using a list of registered hospitals with the State of Kerala and was tagged to the geo-surface. So far, the data sources described are sources that are not directly related to the floods themselves.

The active data that communicates information about the disaster in this case was the AWS and the SAR satellite data. The AWS data was consumed as an API within the cloud-computing platform. Given that the AWS data is geolocation-based, the information within the AWS data could be transposed over the already established pre-disaster sources of information captured using the GIS. This was followed by layering the SAR satellite data, which provides the ability to detect surface water and also provides the images of the ground reality in terms of possible routes for access to the affected. The big data analytics algorithms were deployed over the SAR satellite imagery to calculate the surface water. The calculated surface water was compared against the so far established GIS and AWS data to realise the ground truth of the water inundation.

The results were displayed on a dashboard with simple representations such as heatmap for priority rescue zone, spread of water over time, and the height of water surface spread over the geography of the State of Kerala being able to be filtered over time. Figure 2 provide sample composite image of the computed results displayed to the end-user. Figure 2a (flooding until 14 August 2018) and Fig. 2b (flooding until 21 August 2018) showcase the change in the spread of flooding.

6 Results and discussion

The satellite data analytics platform was adopted by the Government of Kerala officials who were in-charge of the humanitarian relief operations for the identification of the locations that needed high-priority rescue support. Using the satellite data analytics platform developed through the fusion of the data from the different sources explained above, successful rescue missions were conducted across the state. Achieving granularity is one of the key aspects expected from the implemented solutions for developing robust humanitarian supply chain models (Anparasan and Lejeune 2018). Satellite big data analytics based solution for conducting humanitarian relief operations provides the required high level of granularity. To provide concrete evidence of the novelty and the granularity of the satellite big data analytics



(a) (b)

Fig. 2 Composite images post computation from the dashboard: **a** image on 14 August 2018, **b** image on 21 August 2018. (Color figure online)

based solution deployed for the case of Kerala floods, we refer back to the legacy technologies that were used to support the humanitarian relief operations during the flooding that occurred in the State of Uttarakhand in India (prior to the one in Kerala).

An incident report by National Institute of Disaster Management of the Government of India showcases mainly three streams of technologies to be deployed for conducting humanitarian rescue operations in the case of the Uttarakhand flash floods. Since the surface communications were lost, satellite phones were deployed to help coordinate communications between the teams involved in the humanitarian relief operations. Social media (e.g. Facebook and Twitter) accounts were used to log updates of the operations and to take backup of the log of operations. A ‘missing persons’ database was created for Missing Persons Cell to coordinate the location of people affected (Satendra et al. 2014). The report clearly indicates that the humanitarian relief operations were mainly conducted through the joint effort of agencies from Government of India and institutions from State Government that focussed mainly on physical search and rescue operations. Weather was being monitored through the

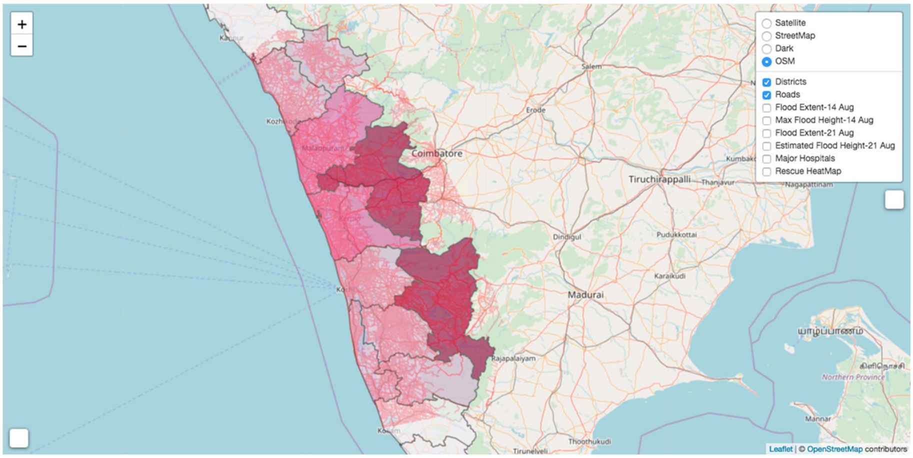


Fig. 3 Basemaps of the State of Kerala. (Color figure online)

updates from Indian Meteorological Department and this data was used to identifying the geography of the affected human settlements. This also reflects that the use of data was mainly done as islands and no fusion of data was done to draw holistic insights for the rescue efforts. Therefore, from a standpoint of deploying ICTs for humanitarian relief operations, we can conclude that the technology utility in the Uttarakhand flash floods case was broadly for probabilistic identification of affected human settlements and communications coordination between humanitarian actors themselves.

The above-cited report does put forth recommendations that are in the interest of this study. It included the need for landslide risk zonation mapping, need for improving the accuracy of risk mapping by considering weather, glacial lakes, river flow monitoring, and finally the development of an incident response system that shall allow to support the local command and coordination structures during an emergency. In comparing the Uttarakhand and Kerala incidents, we would like to argue that the technology deployment as a part of the ICT preparedness has had no change. However, the key change is in the adoption of big data analytics as an independent ICT infrastructure that brings together the separate islands of data to create value for decision-makers in humanitarian relief operations.

All the data sources used as a part of the ICT deployment in the case of Kerala floods had no prior special dedicated investment as a part of the disaster management charter. Figure 3 presents the visualisation shown on the dashboard for the basemap of the State of Kerala. DEM data layer is fused on top of this basemap to provide a full three-dimensional pre-disaster geo-surface knowledge of the State of Kerala. This knowledge of the geography was extended to establishing the spread of the population within the area of interest by layering the census information sourced from the Government of Kerala. These three layers combined provided a concrete pre-disaster picture of both the geography as well as the spread of the population. Contrasting this pre-disaster picture with accurate sources of information on the disaster affected regions accelerates the humanitarian relief operations. We believe that much of the agility in humanitarian relief operations comes from having the ability to spread accurate post-disaster information of relevance to all humanitarian actors involved.

Figure 4 shows a layer of all hospitals across the State of Kerala geolocated and tagged in the GIS to help humanitarian relief operation teams to transport any disaster victims needing medical attention to the nearest functioning hospitals. This information also allows

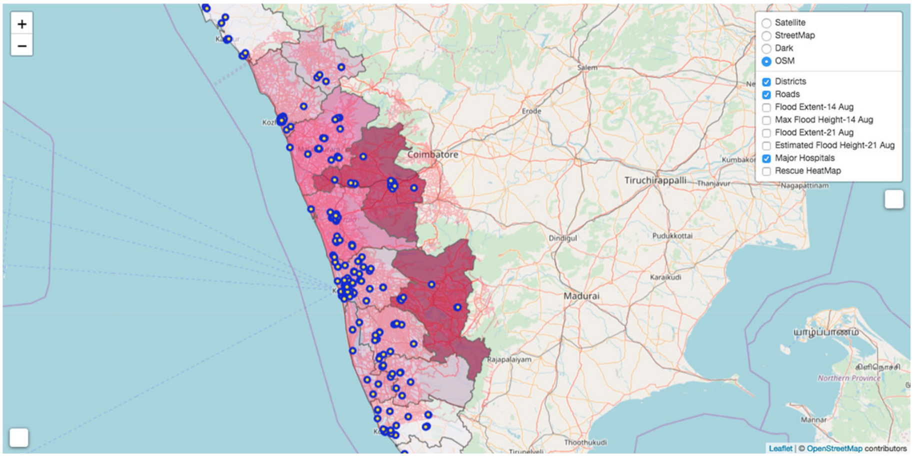


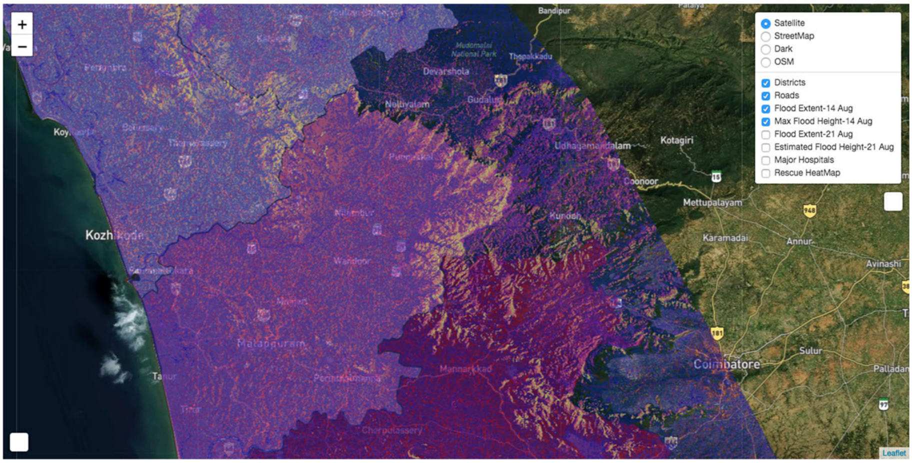
Fig. 4 Analytics dashboard with major hospitals tagged. (Color figure online)

identification of hospitals that may need immediate rescue operations based on the levels of indentation of water.

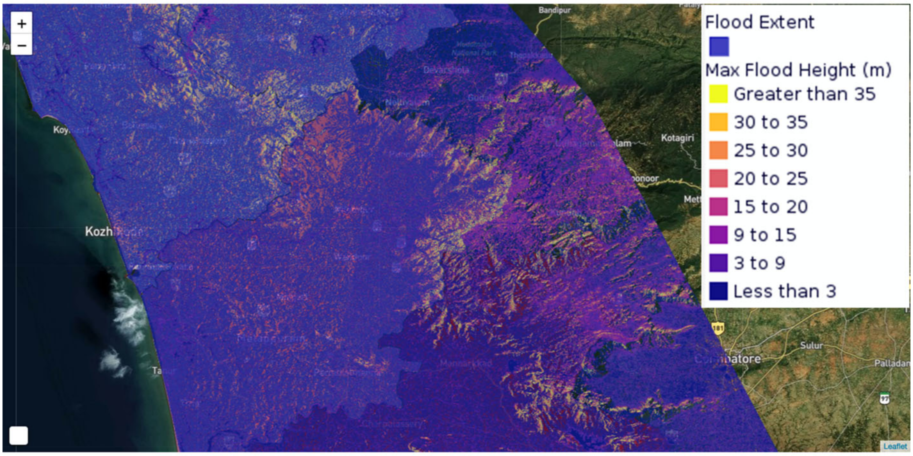
The described data so far are pre-disaster sources of information, which acts as the baseline GIS. This baseline GIS is deployed on a commercial cloud-computing platform over which active data relating to the floods are fused. Within the context of agility in humanitarian relief operations, providing access to such a common ICT platform allows humanitarian planners across different organisations and teams they are coordinating with to carry out their respective efforts in a synchronized fashion.

The AWS data captured from the onset to the end of the floods between 8 and 21 August allowed to create a profile of the rainfall indentation. This led to the visualisation of the amount of rainfall over the geographical profile of the State of Kerala. The AWS data is consistent with the amount of rainfall, but does not allow to capture the surface water spread over the geography accurately. This was established by using the SAR satellite data. The big data analytics algorithms were deployed over the SAR satellite imagery to detect the surface water. This was compared against the so far established GIS and AWS data to realise the ground truth of water inundation. The same source of data was used to map the flooding over established roadways to create navigation routes for the rescue teams. This enabled the rescue teams to reach the closest possible locations before makeshift vessels (such as rescue boats) could be used.

Figure 5 provides the change in rain intensity spread over the entire geography of the State of Kerala between the second and the third week of August 2018. Figure 5a depicts the total spread of the rainfall up to 14 August 2018 and Fig. 5b depicts the spread of the rainfall through to 21 August 2018. The intensity of the rainfall over the geography is colour coded with blue being below 3 m to yellow with over 35 m as shown in the legend of Fig. 5b. For computing the identification of high-risk areas using big data analytics algorithms, spread of the water in flood risk areas was processed on a commercial cloud-computing platform. The results of the analytics were deployed on a simple web-based dashboard for ease of access to the results. This ensured that there is marginal effort spent on training the humanitarian relief operations teams to understand the output of the analysis and allowed them to act on the results swiftly to execute rescue missions.



(a)



(b)

Fig. 5 Rainwater spread and water height: **a** image as on August 14, 2018, **b** image as on August 21, 2018. (Color figure online)

Figure 6 provides the result of the analytics process showcased on a web-based dashboard to the humanitarian relief operation teams to help them easily identify the most critical locations that need quick support. The green-yellow patches in the image depict the geolocation of the most critical locations where water inundation was the highest and posed major risk to life and property. Even with the persistent cloud cover over the course of the two weeks, the satellite imagery discretely mapped surface water. This information contrasted against the terrain information and the AWS measurements allowed the determination of the height of the water surface over the course of the entire flooding period. The zoning of the flood risk over the geography using the census data allowed keeping track of the water indentation in major clusters of populated areas. Finally, relief operation planners used satellite big data analytics platform for planning humanitarian logistics. This was accomplished by establishing route maps based on total surface water indentation over the geography. The logistics planners

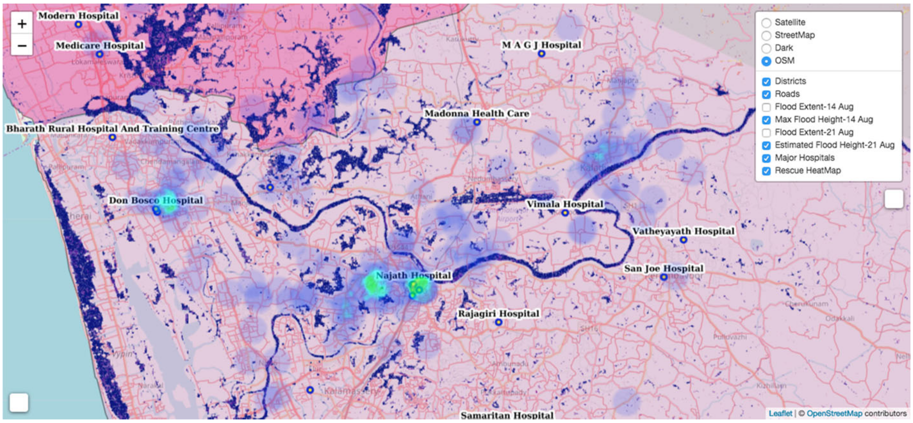


Fig. 6 Analytics dashboard with a rescue prioritisation HeatMap. (Color figure online)

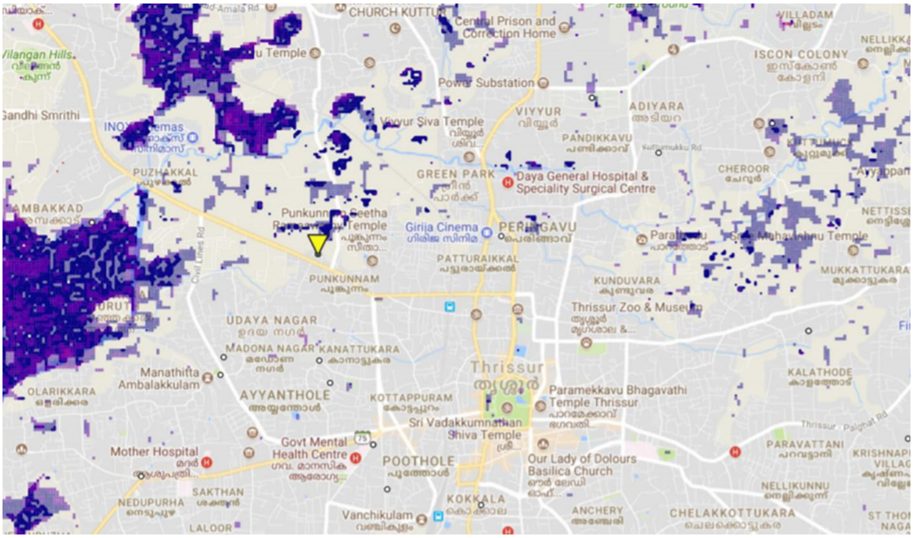


Fig. 7 Locating distressed people through geo-coding (yellow marker designates the location). (Color figure online)

could then create approach routes for a designated geography that allowed the rescue teams to reach the locations in the shortest time. Figure 7 is an example of tagging of a rescue location within the platform which logistics planners can act upon. This augurs with the call to advance foresight into real time collaboration in disaster management (Weber et al. 2015).

In the previous section, we documented the different sources of the data to indicate their value in the context of humanitarian relief operations. It is important to note that the agility in humanitarian relief operations comes from not depending on just individual sources of data, but rather from fusion of various complimentary datasets for holistic decision-making. For example, the satellite data helps in the assessment of the pre-event and the post-event situation of the affected regions and can help plan logistics routes. However, it does not provide information on the rainfall spread over the geography of interest from the onset of the showers to be able to accurately geolocate areas of highest intensity. These data sets are independent and complimentary. The value of the information when these datasets are fused together is much higher than when considered individually.

The real-life case of multiple floods in India (including Kerala) showcase restrictive boundaries in transferring established practices from commercial supply chains to humanitarian activities. Theoretical frameworks need to provide a more focussed analysis based on multiple real-life incidents. They often stop at simplistic suggestions on emulating practices in commercial supply chains to humanitarian supply chains. Frameworks that can assess and contextualize agility in humanitarian relief operations based on different cases (such as no communications available with the affected, partial communications available and all communications available) will be beneficial for theory development. Concepts such as agility are still unexplored as central topics in research under humanitarian relief operations. We see opportunity to use both cross-sectional and longitudinal studies to provide systematic insights by focussing solely on agility.

In the process of studying the use of the satellite big data analytics, we realised that greater challenges exist in capacity building among all humanitarian actors to adopt the ICT solutions. Researchers often study one particular incident and derive insights based on the use of ICTs for the affected (e.g. use of social media in floods to help the affected). However, there seems to be a dearth of research that focus on the capacity building for the adoption of ICTs among humanitarian actors. Shifting the frame of reference from the use of ICTs for relief operations to theory development on capacity building of humanitarian actors for adopting novel ICTs (in especially developing countries like India) will be of value.

We are also of the opinion that such rapid diffusion of information addresses uncertainty and complexity in humanitarian relief operations without limitations. For example, social media is often cited as a contributor to humanitarian relief operations, which allows the crowd-participation. Internal diffusion of information through social media networks move at a significantly higher speed than the diffusion of information that are arising from external sources to these networks (Yoo et al. 2016). Integrating sources like social-media without having the ability to gather real-time updates to the shared information may actually increase uncertainty and lead to the reduction in agility of humanitarian relief operations. Supporting this claim, a journalist working as a humanitarian volunteer during the floods in India recalled how wide circulation of social media posts after few days from their initial post led to rescue teams visiting locations where rescue operations were already executed (Rajendran 2018). Therefore, there is immense potential in using novel ICTs in humanitarian relief operations. However, it has to be approached with the information asymmetry caveat that comes along with these sources of data being treated effectively. Data will remain a dual-edge sword and its source, quality, interpretation and the lifespan will largely drive its contribution to improving the agility in humanitarian relief operations.

Our case study extends the argument provided by Behl and Dutta (2018) for researchers to study the success or failure of relief operations. The case study establishes the foundation for the use of satellite big data analytics alongside the citizen level mitigation efforts as suggested by Choudhary and Vyas (2020). The case of the response to the floods in Kerala addresses the criticality of response time in relief operations which is highlighted by Owusu-Kwateng et al. (2017). From the context of fit to the Indian disaster relief operations, the use of satellite big data analytics showcased in this case study ties itself into filling the gaps in experiences from Uttarakhand and Jammu and Kashmir discussed by Kabra et al. (2015) and Dey (2017) respectively.

7 Conclusion

Several disasters have proven their ability to disrupt established ICT infrastructure. This disruption have shown to obstruct the channel for gathering real-time information directly from the communities affected by disasters. By hampering the agility of humanitarian supply chains, this creates a complex, chaotic, uncertain, and restrictive environment for humanitarian relief operations. In this research, we present a solution to the described problem by pointing to the ability of satellite big data analytics to facilitate humanitarian relief operations with the deployment of novel ICTs, which do not rely on traditional ICT infrastructure of legacy systems. Using a case study based on the relief operations during the Kerala floods of August 2018, we validated how a novel ICT using big data analytics algorithms on different sources of information including satellite imagery, GIS, AWS, census data and mobile phone logs contributed in effectively prioritizing rescue operations. Initially raised research question is answered through the case study conducted by showcasing the integration of satellite big data analytics to bridge the gap left by the absence of disaster preparedness-oriented ICT infrastructure and thereby contribute towards improving the agility in humanitarian relief operations. The analytics platform made available to the stakeholders involved in the rescue operations led to timely logistical planning and execution of rescue missions. Platform developed improved the accuracy of information between the distressed community and the stakeholders involved and thereby increased the agility of humanitarian logistics and relief supply chains. The present case proves the utility of fusing data sources on a simple dashboard that are normally sitting as islands of information. It is evident that the fusion of data sources using big data analytics led to the enrichment of the overall quality of insights to humanitarian relief operation teams, thereby contributing to increasing their agility.

7.1 Research implications

As indicated earlier, management research has highlighted problems in coordination among stakeholders in humanitarian relief operations. Decision support systems in humanitarian relief operations point to the benefits of incorporating information and decision parameters into the tactical planning to enhance responsiveness (Laguna-Salvadó et al. 2018). Through this case study, we highlighted the problems in coordination within the ICT usage in humanitarian relief operations. The dependence on ICTs for humanitarian relief operations is increasing and coordination within ICT tools has an impact on the agility of the humanitarian relief operations.

We believe ICT rollout has been often dealt in silos, where one piece of the puzzle is solved by introducing a particular technology. Some examples include Internet of Things (IoT) for enhancing emergency response operations (Yang et al. 2013), Radio Frequency Identification Devices (RFID) for inventory management (Ozguven and Ozbay 2015), development of a dedicated software for humanitarian logistics (Gatignon et al. 2010), creation of virtual information centre for enabling the coordination and processing of information requests for the stakeholders (Bui and Sankaran 2001), and handheld devices used in camp management (Ergun et al. 2014). One could refer the underlying data gathered in each of these ICT implementations as 'data islands', which have no spill over across each other. There is tremendous value for humanitarian supply chain management theory in studying the possible collation of such data streams across the entire cycle of humanitarian disaster management from preparedness, training to rescue, relief and recovery operations to build agility in ICT platforms.

Through this case study, we do not claim that fixing ICTs will leapfrog agility in humanitarian relief operations. We acknowledge the fact that apart from the technological infrastructure, structural barriers and differences in organizational cultures contribute to the gaps in information flow within existing networks. Such gaps widen due to the breakdown of communications during humanitarian disasters and therefore lead to hindrance in decision making that create problems in cooperation among the stakeholders (Palttala et al. 2012). We only exhibit how novel ICTs enabled with big data analytics can bridge such gaps to execute humanitarian relief operations in an agile fashion.

7.2 Practice implications

Within the context of this study, there are already calls for integration of machine learning into humanitarian applications for actively participating in relief operations by using satellite data as the primary source with other secondary data streams to train algorithms (Quinn et al. 2018). These are essentially new layers of technologies being adopted as a part of ICTs supporting humanitarian relief operations to smoothen the processes involved. There is scope for analytics focussed ICTs to have horizontal (new data sources fused) and vertical (preparedness, logistics, recovery, etc.) scaling to enhance the quality of insights derived by using such tools to support humanitarian relief operations. There is scope for creative curation by the humanitarian relief operations community for a larger participation of commercial entities in making the gathered data available on a priority and possibly open-access basis to increase the agility of ICT tools. An example in this regard is the 'Open Data Program' announced by commercial high-resolution satellite imagery company DigitalGlobe that provides open imagery for select sudden onset of major disasters into the public domain under a Creative Commons 4.0 license. This enables the humanitarian community to use its library of pre-event and post-event imagery for damage assessment and integration into humanitarian response technologies. There is also scope to integrate new assets in space recently launched by India itself. Satellites by the Indian Space Research Organisation (ISRO) introduce an opportunity to provide both communication and imagery support in disaster relief operations (Press Information Bureau 2017). They can provide ability to request satellite data of affected independently and contribute to expeditious decision-making in rescue operations.

7.3 Limitations

In the present case, the officials of the State Government of Kerala chose to quickly adopt the satellite big data analytics as an ICT tool in humanitarian relief operations, specifically to use the platform to prioritize rescue operations. Since the decision of adoption of the technology came directly from the principal authorities responsible for the rescue, relief and recovery efforts, there was notable trust on the decision intelligence arising out of the analytics platform. The top-down adoption also allowed taking quick decisions on sending rescue teams to specifically identified zones through the platform and led to carrying out swift operations. As training is needed for other critical humanitarian relief actors such as non-governmental or military personnel to adopt new tools (Heaslip et al. 2012), the scalability of this solution is still to be tested with these actors. Due to the top-down nature of the adoption of the ICT for humanitarian relief operations in this particular case study, we are not in a position to comment on the cross-coordination of the teams across different stakeholders. From a methodological stand point, our case limits to using single incident in a single geography to address the research question. The application showcased is also focussed on floods as a source of disaster. The implications for other types of disasters need to be studied.

7.4 Future research

Humanitarian relief operations and the entire cycle of disaster management have been depending largely on human decision-making. There is immense scope to study the effects of introducing new technologies in ICTs such as machine learning (Ofli et al. 2016), artificial intelligence (Imran et al. 2014) and augmented reality (Iguchi et al. 2016). The implementation of such ICTs in the realm of humanitarian relief operations can have an impact on the agility of disaster alert/preparedness operations, can demand reengineering of traditional humanitarian supply chain models, and may bring new challenges on the ethical grounds.

There have been appreciable efforts of ordinary citizens involvement to increase the agility of humanitarian relief operations. It includes crowd-sourced efforts of integration of social media (Wukich and Mergel 2015), verification of contradictory information emerging out of crowd-sourced information (Popoola et al. 2013), etc. The assessment of such volunteered ICT efforts are criticised because the risks associated with information outweighs the benefits of its use (Goodchild and Glennon 2010). However, there are new calls for gamification of such efforts to bring in agility and efficiency to the entire cycle of disaster management from preparedness (Meera et al. 2016) to conducting humanitarian relief operations (Schimak et al. 2015). There is also scope to extend the agility in relief operations of other disasters like forest fires, landslides, and drought using satellite big data analytics.

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